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Performance assessment of CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA precipitation products across India

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ABSTRACT

Accurate long-term estimates of precipitation at fine spatiotemporal resolution are vital for several applications ranging from hydrometeorology to climatology. The availability of a good network of rain gauges, and high precipitation variability associated with two annual monsoon systems and complex topography make India a suitable test-bed to assess the performance of any satellite-based precipitation product. This study assesses the performance of latest versions of four multi-satellite precipitation products: (i) Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), (ii) Multi-Source Weighted-Ensemble Precipitation (MSWEP), (iii) SM2RAIN-Climate Change Initiative (SM2RAIN-CCI), and (iv) TRMM Multisatellite Precipitation Analysis (TMPA) across India using gauge-based observations for the period of 1998–2015 at monthly scale. These four multi-satellite precipitation products are essentially based on different algorithms and input data sets. Among these multi-satellite precipitation products, SM2RAIN-CCI is the only product that does not use rain gauge observations for bias adjustment. Results indicate that CHIRPS and TMPA are comparable to gauge-based precipitation estimates at all-India and sub-regional scales followed by MSWEP estimates. However, SM2RAIN-CCI largely underestimates precipitation across the country as compared to gauge-based observations. The systematic error component in SM2RAIN-CCI dominates as compared to random error component, which suggests the need of a suitable bias correction to SM2RAIN-CCI before integrating it in any application. The overall results indicate that CHIRPS data set could be used for long-term precipitation analyses with rather higher confidence.

1. Introduction

Precipitation is one of the most important atmospheric variables of the global energy and water cycle. Reliable long temporal record of global precipitation at fine spatiotemporal resolution is crucial for a wide range of applications such as for crop modeling, hydrometeorology, water resources management, flood and drought monitoring, and climatological applications. Although ground-based rain gauge observations provide accurate measurement of precipitation locally, their limited spatial representativeness and inhomogeneous distribution constraint its applicability at global scale (Kidd et al., 2017). Alternatively, multi-satellite precipitation estimates take relative advantages of contemporary constellation of precipitation-related infrared and microwave satellite sensors and offer a unique opportunity to study the high spatiotemporal variability of precipitation at global scale (Kucera et al., 2013; Adler et al., 2017; Sun et al., 2018). The satellite-based precipitation estimation techniques improved substantially after the successful launch of the Tropical Rainfall Measuring Mission (TRMM) satellite and consequently several multi-satellite precipitation products were developed at high spatial and temporal resolutions. Some of the popular TRMM-era high resolution multi-satellite precipitation products are TRMM Multisatellite Precipitation Analysis (TMPA) (Huffman et al., 2010), Climate Prediction Center (CPC) Morphing (CMORPH) (Joyce et al., 2011; Xie et al., 2017), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) (Sorooshian et al., 2000; Nguyen et al., 2018), Naval Research Laboratory – Blended (NRL-blended) (Turk and Miller, 2005), and Global Satellite Mapping of Precipitation (GSMaP) (Ushio et al., 2009; Mega et al., 2018). However, a comprehensive evaluation of these multi-satellite precipitation products at distinct spatial and temporal scales is essential for their use in practical applications (Behrangi et al., 2016; Gehne et al., 2016; Maggioni et al., 2016; Camici et al., 2018).

India receives substantial precipitation due to two large-scale monsoon systems – southwest (June – September) and northeast (October – December) monsoons every year, which exhibit pronounced spatio-temporal precipitation variability associated with complex topography. After the launch of Kalpana-1 satellite in 2002 by the Indian Space Research Organisation, several precipitation retrieval algorithms were developed for precipitation estimation over India and adjoining regions (Gairola et al., 2014). These infrared-based precipitation products were successfully utilized for monsoon rainfall monitoring and meteorological drought assessment across India (Mahesh et al., 2014; Patel et al., 2015; Bushair et al., 2016). These precipitation retrieval algorithms were also

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implemented at INSAT-3D satellite measurements, which provide improved precipitation estimates at finer spatial resolution as compared to Kalpana-1 estimates (Mitra et al., 2018; Singh et al., 2018). However, infrared-only satellite precipitation products underestimate orographic precipitation. Additionally, India has an appreciably good network of rain gauges well-spread across the country (Pai et al., 2014).

The TRMM-based multi-satellite precipitation products were extensively evaluated across India using gauge-based observations and better performance of TMPA product as compared to other TRMM-era multi-satellite precipitation products were reported (Prakash et al., 2014, 2015a, 2015c, 2016b, 2018b; Rana et al., 2015). After the launch of the Global Precipitation Measurement (GPM) Core Observatory in 2014, an advanced finer resolution multi-satellite precipitation product namely, Integrated Multi-satellitE Retrievals for GPM (IMERG) (Huffman et al., 2018) has been released. This multi-satellite precipitation product takes the relative advantages of TMPA, CMORPH, and PERSIANN algorithms. A preliminary assessment of this GPM-based multi-satellite precipitation product showed better performance than TMPA across India (Prakash et al., 2016a, 2018a, 2018b), as expected due to advancement in sensors and algorithm. However, the temporal record of IMERG is limited due to its availability since 2014. TRMM-based multi-satellite precipitation products are available since 1998, which limit their use for climatological applications. Only two multi-satellite global precipitation products – Global Precipitation Climatology Project (GPCP) (Adler et al., 2003) and CPC Merged Analysis of Precipitation (CMAP) (Xie and Arkin, 1997) have temporal coverage beginning from 1979. However, both products have rather coarser spatial (2.5° latitude × 2.5° longitude) and temporal (monthly) resolutions. To bridge the gap of availability of high-resolution global multi-satellite precipitation products prior to 1998, the Multi-Source Weighted-Ensemble Precipitation (MSWEP) (Beck et al., 2017a, 2018), and Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Funk et al., 2015) products were developed. Furthermore, a new precipitation product – SM2RAIN-Climate Change Initiative (SM2RAIN-CCI) (Ciabatta et al., 2018) has been recently released, which estimates precipitation directly from surface soil moisture observations for the first time. Hence, it becomes essential to compare these three high-resolution precipitation products with TMPA product and gauge-based observations for their widest usage and applicability.

The objective of this study is to assess the performance of latest versions of CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA products across India against gauge-based observations. Even though IMERG performs better than TMPA over India, IMERG is not considered in this study due to its limited temporal record. The evaluation is performed at 0.25° spatial resolution and at a monthly scale, due to available spatial resolution of gauge-based gridded data set and differences in daily precipitation accumulation conventions among these products, for the period of 1998–2015. It is to be noted that CHIRPS, MSWEP, and TMPA products use gauge observations for bias adjustment, whereas SM2RAIN-CCI does not incorporate any gauge-based bias correction.

2. Data and methods

2.1. Precipitation data sets

For the assessment of satellite-based precipitation estimates, rain gauge derived gridded precipitation product at 0.25° spatial resolution (Pai et al., 2014) has been used as reference. This gridded gauge-based daily precipitation product is developed by the India Meteorological Department (IMD) using a reasonably good network of surface rain gauges across India and proven to be optimal for various hydrometeorological and climatological applications. Fig. 1 shows the spatial distribution of IMD rain gauges for the month of July 2014. It can be seen that the gauges are well spread across the country except over the northern and northeastern parts. The number of reported gauges also varies at daily scale (Pai et al., 2014). The other available gauge-based global precipitation data sets use only a fraction of gauge observations across the country due to availability constraint. IMD uses 2000–3500 rain gauge observations for the preparation of gridded

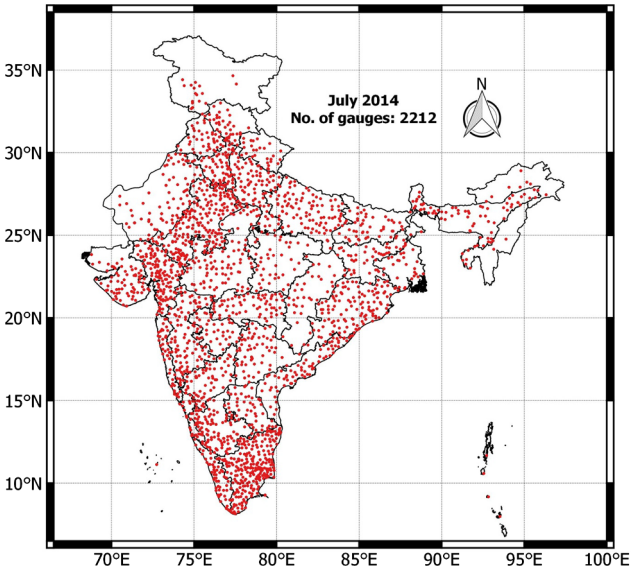

Fig. 1. Spatial distribution of IMD rain gauges over India during the month of July 2014. These rain gauges provided consistent observations during this month.

precipitation product for the period of 1998–2015 (Pai et al., 2014), whereas TMPA and other gauge-adjusted multi-satellite precipitation products use 300–400 gauge observations over India (Prakash et al., 2015d).

Four multi-satellite precipitation products namely, CHIRPS, MSWEP, SM2RAIN, and TMPA for the period of 1998–2015, based on common period of availability of each precipitation data set, have been used in this study. The CHIRPS is a quasi-global (50°S-50°N) long-term precipitation data set developed by the United States Geological Survey (USGS) and Climate Hazards Group (CHG) for trend analysis and seasonal drought monitoring. This gridded land-only precipitation data set is developed by the synergistic use of satellite infrared cold cloud duration measurements and ground-based rain gauge observations (Funk et al., 2015). The latest version 2.0 (V2.0) of this precipitation data set is available for 1981–2017 at 0.05° spatial resolution and at daily, pentad, and monthly time scales.

The MSWEP is a global historic precipitation data set available at 0.1° spatial resolution and at three-hourly, daily, and monthly temporal resolutions. This precipitation data set utilizes the relative merits of satellite infrared and microwave precipitation estimates, rain gauge observations and reanalysis products (Beck et al., 2017a, 2018). Version 2.1 (V2.1) of this precipitation data set is available for 1979–2016. In a recent evaluation of 22 precipitation products at global scale using rain gauges and hydrological modeling, MSWEP product was shown to be one of the best performer (Beck et al., 2017b).

The SM2RAIN-CCI is a global daily precipitation data set available at 0.25° spatial resolution for the period of 1998–2015 (Ciabatta et al., 2018). This precipitation product is developed from the European Space Agency (ESA) Climate Change Initiative combined active and passive microwave satellite soil moisture product (Dorigo et al., 2017) through SM2RAIN algorithm. SM2RAIN algorithm is a novel technique to directly estimate precipitation from surface soil moisture measurements through soil water balance equation (Brocca et al., 2014).

The TMPA is a quasi-global (60°S-60°N) precipitation data sets available at 0.25° spatial resolution and at three-hourly, daily, and monthly temporal resolutions. This precipitation product is available in near-real time and delayed/research modes. The TMPA research version 7 (V7) product used in this study uses satellite infrared and microwave precipitation estimates along with gauge observations over land (Huffman et al., 2010). This precipitation product has been proven to be one of the best TRMM-era multi-satellite precipitation estimates (Maggioni et al., 2016; Prakash et al. 2018a). TMPA precipitation product also showed potential for meteorological drought monitoring

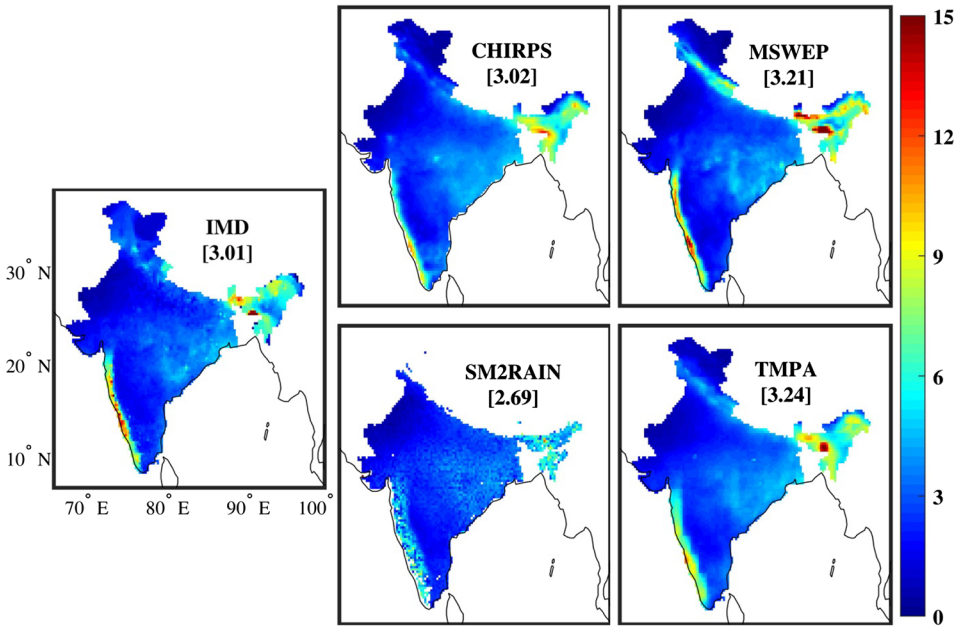

Fig. 2. Spatial distributions of 18-year (1998–2015) mean precipitation (mm day^{-1}) across India from the IMD, CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA products. All-India mean values are also provided for each precipitation product.

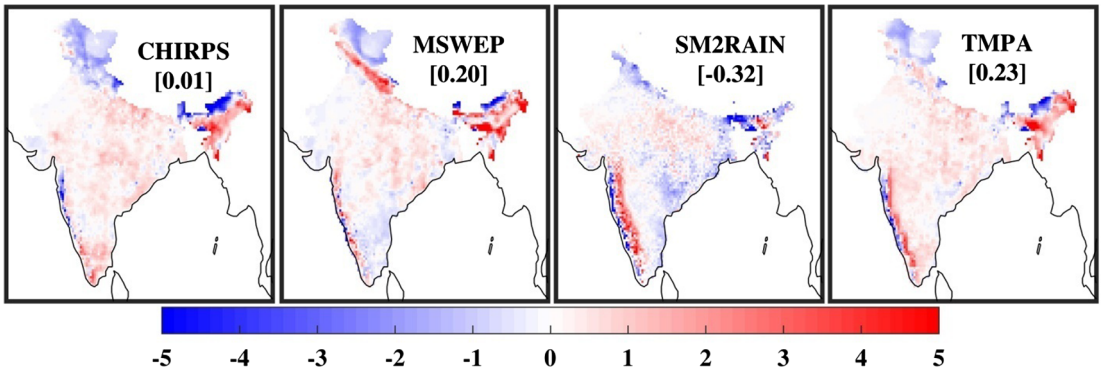

Fig. 3. Spatial distributions of bias in monthly precipitation (mm day^{-1}) derived from CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA products with respect to IMD gauge-based data for the period of 1998–2015. All-India mean values of biases are also provided for each precipitation product.

across India (Prakash, 2018).

2.2. Methodology

As CHIRPS and MSWEP precipitation products are available at 0.05° and 0.1° spatial resolutions respectively, both data sets have been re-sampled at 0.25° spatial resolution, similar to reference data, for the comparison. Moreover, IMD accumulates daily precipitation ending at 0300UTC, which is quite different from the satellite daily precipitation accumulation convention. There is a need of sub-daily (e.g., hourly, three-hourly) satellite-derived precipitation estimates for a meaningful comparison with the IMD gauge-based data across India at a daily scale (Prakash et al., 2015a). Hence, the assessment of multi-satellite precipitation products was carried out at monthly scale. For this purpose, daily precipitation products were averaged to a monthly scale.

Five state-of-the-art continuous statistical metrics viz., mean, bias, coefficient of variation (CV), Pearson's correlation coefficient (r), and root-mean-square error (RMSE) were computed at each grid across the country for the study period. Moreover, systematic and random error components of the satellite-derived precipitation products were assessed through a suitable error decomposition technique (AghaKouchak et al., 2012; Prakash et al., 2015b). A critical determination of these error components is crucial for the product developers and end users. These error metrics are defined as

$$r = \frac{\sum_{i=1}^{n}(G_i - G)(S_i - S)}{\sqrt{\sum_{i=1}^{n}(G_i - G)^2 \sum_{i=1}^{n}(S_i - S)^2}} \quad (1)$$

$$Bias = S - O \quad (2)$$

$$CV = \frac{\sqrt{\frac{\sum_{i=1}^{n}(S_i - S)^2}{n}}}{S} \times 100\% \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_i - G_i)^2}{n}} \quad (4)$$

$$Random\ Err. = \frac{\sum_{i=1}^{n}(S_i - S_i^*)^2}{n} \quad (5)$$

$$Syst.\ Err. = \frac{\sum_{i=1}^{n}(S_i^* - G_i)^2}{n} \quad (6)$$

$$\text{with } S_i^* = a \times G_i + b \quad (7)$$

Here S_i denotes satellite-derived precipitation, G_i denotes IMD gauge-based precipitation, S and G be their respective mean, and n be the number of collocated observations. The ideal values for bias, RMSE

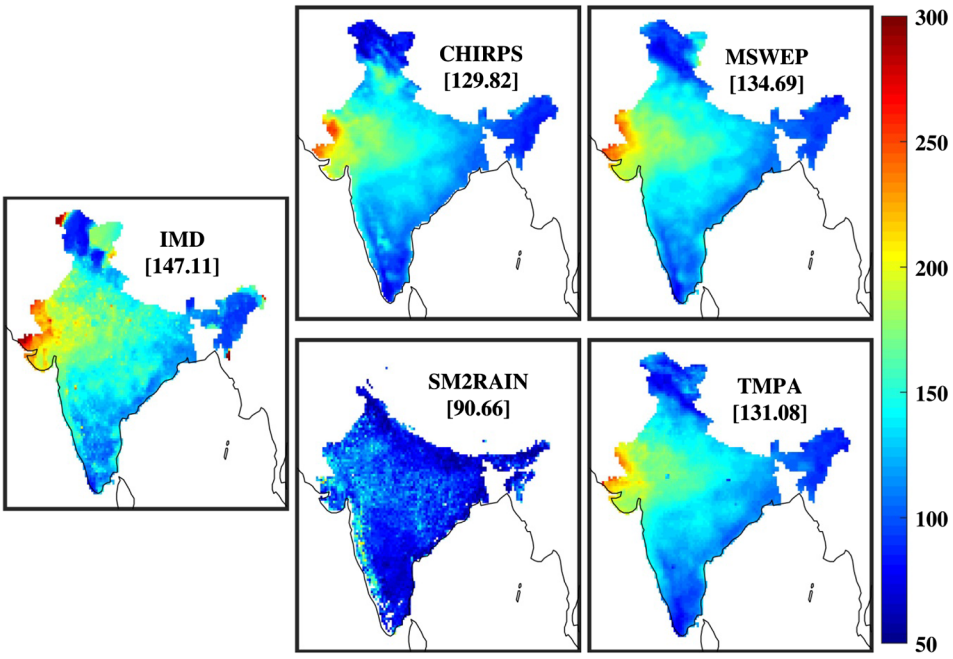

Fig. 4. Spatial distributions of coefficient of variation (%) in monthly precipitation across India from the IMD, CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA products for the period of 1998–2015. All-India mean values of CV are also provided for each precipitation product.

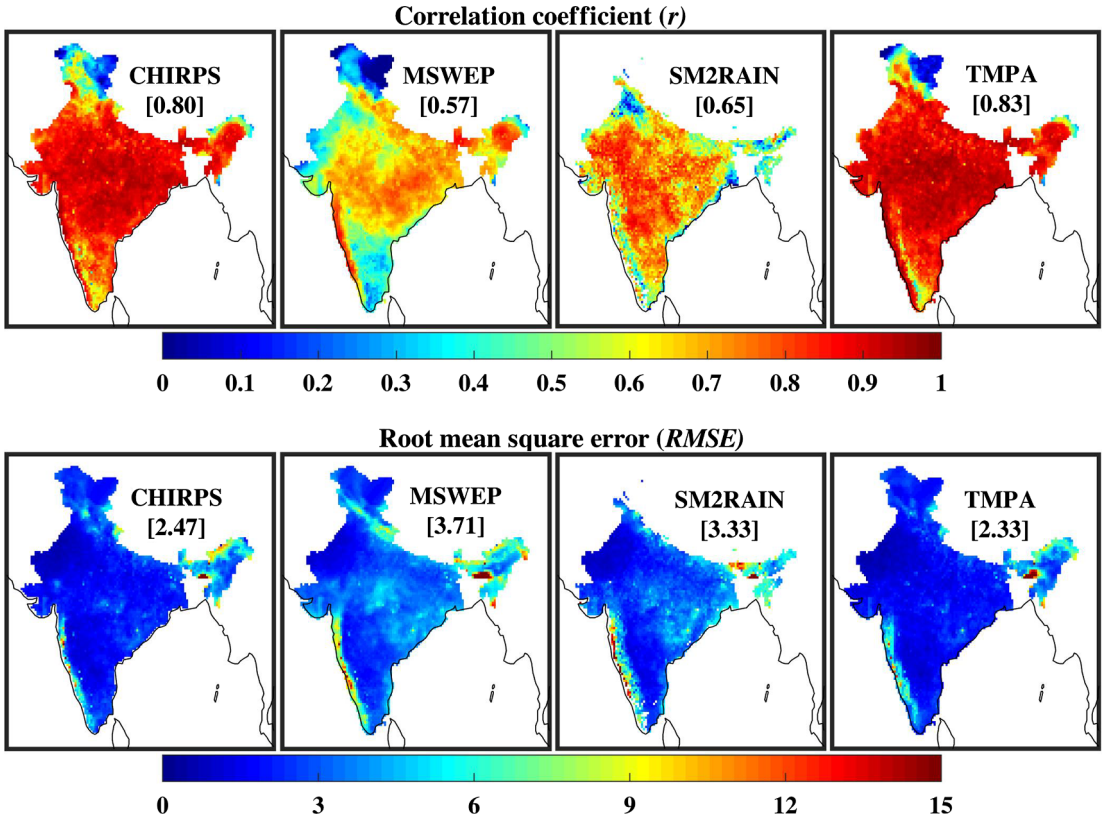

Fig. 5. Spatial distributions of correlation coefficient (top panel) and RMSE (mm day^{-1}; bottom panel) in monthly precipitation across India from CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA products as compared to IMD gauge-based data for the period of 1998–2015. All-India mean values of correlation coefficient and RMSE are also provided for each precipitation product.

and error components are 0, and the perfect value of r is 1.

In addition, the modified Kling-Gupta efficiency (KGE) score was used to assess the performance of satellite-derived precipitation data sets. KGE combines Pearson's correlation coefficient, bias and variability (Kling et al., 2012), which is defined as

$$KGE = 1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\gamma-1)^2} \quad (8)$$

$$\text{with } \beta = \frac{S}{G} \text{ and } \gamma = \frac{(CV)_S}{(CV)_G} \quad (9)$$

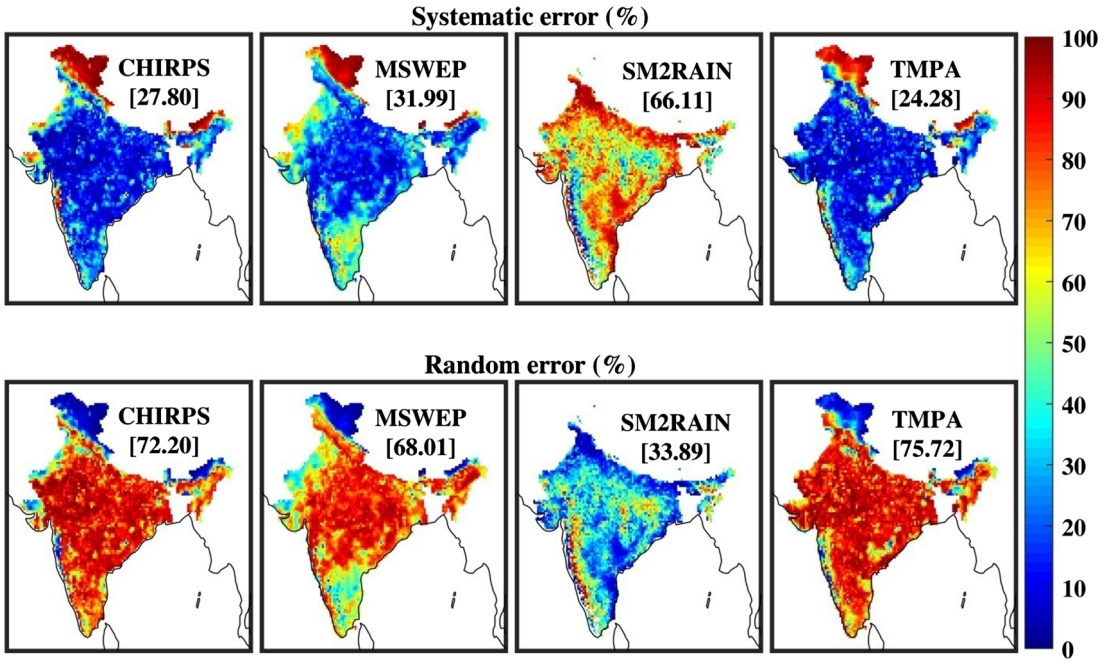

Fig. 6. Spatial distributions of systematic (top panel) and random error components (bottom panel) in monthly precipitation across India from CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA products as compared to IMD gauge-based data for the period of 1998–2015. All-India mean values of both error components are also provided for each precipitation product.

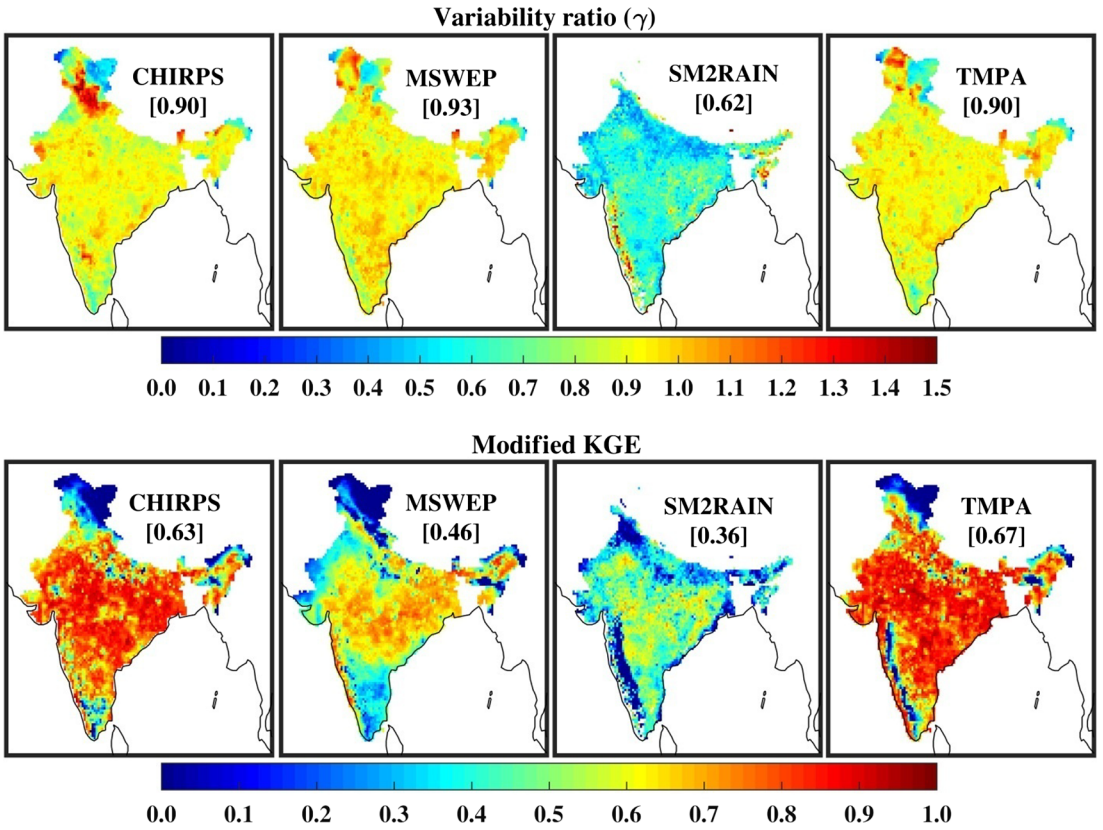

Fig. 7. Spatial distributions of variability ratio (top panel) and modified KGE (bottom panel) in monthly precipitation across India from CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA products as compared to IMD gauge-based data for the period of 1998–2015. All-India mean values of both scores are also provided for each precipitation product.

where β is the bias ratio and γ is the variability ratio. The optimum values of KGE, β and γ are 1.

Furthermore, an empirical cumulative distribution function (CDF) was also computed from each precipitation product to assess the potential of multi-satellite products in estimation of different precipitation ranges. The evaluation was performed at all-India and sub-regional scales as well through domain-mean time-series analysis and Taylor diagram (Taylor, 2001). Three major sub-regions within the

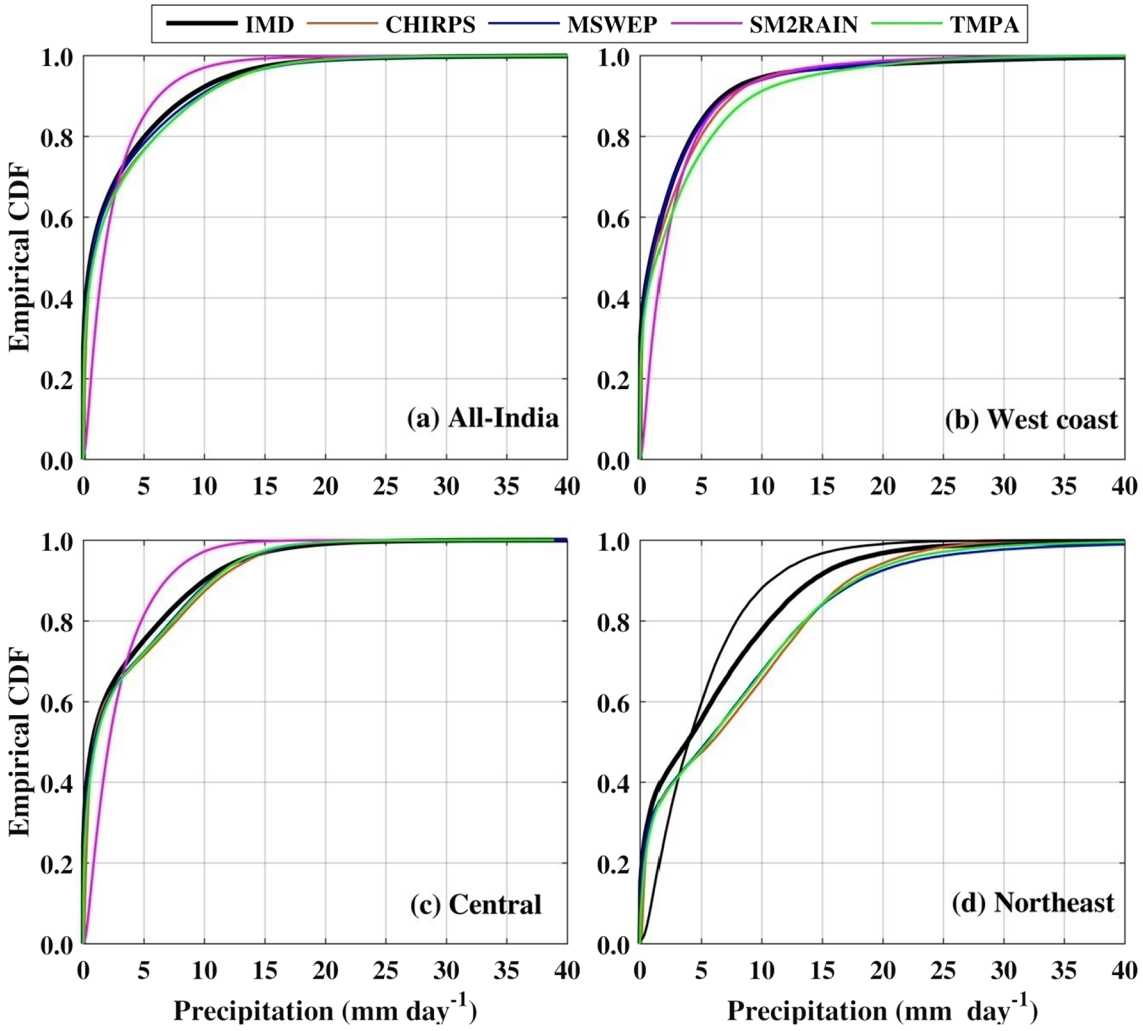

Fig. 8. Empirical cumulative distribution functions of monthly precipitation derived from the IMD, CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA products across (a) all-India, (b) west coast, (c) central, and (d) northeast India for the period of 1998–2015.

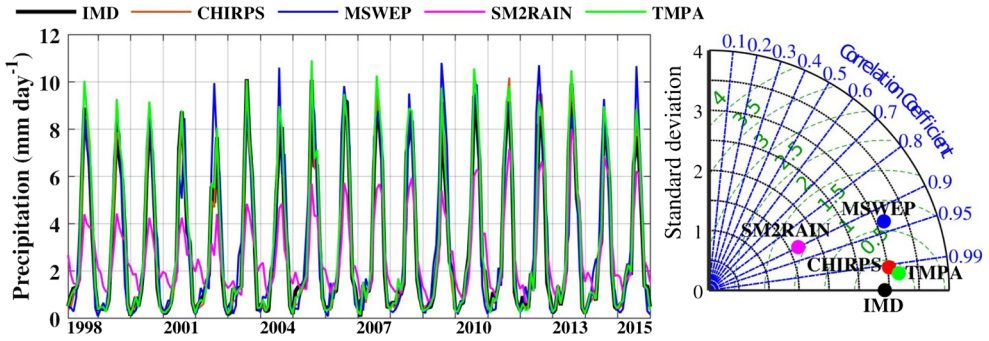

Fig. 9. Time-series of monthly all-India precipitation derived from the IMD, CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA products and corresponding Taylor diagram for the period of 1998–2015.

country: (a) west coast (8°N-20°N & 72.5°E-77.5°E), (b) central (17.5°N-27.5°N & 78°E-88°E), and (c) northeast India (22°N-30°N & 90°E-98°E) were considered for detailed analysis. The west coast and northeast India are complex orographic sub-regions, whereas central India is rather a plain sub-region. All error metrics described above were also computed for all-India and three sub-regions.

3. Results and discussion

Fig. 2 shows the spatial distributions of 18-year mean precipitation across India derived from monthly gauge-based and four multi-satellite products. The well-known precipitation features such as high precipitation areas situated along the west coast, northeast, and central India are captured realistically by the multi-satellite products. However, there are differences in magnitudes among them. The notable precipitation gradients along the west coast are well-captured by the CHIRPS and MSWEP products, possibly due to their availability at higher native spatial resolutions. SM2RAIN-CCI shows wider belts along the west coast getting high precipitation. It is to be noted that SM2RAIN-CCI does not estimate precipitation over the frozen soil, snow

Table 1
Error characteristics of all-India monthly precipitation estimates derived from CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA as compared to IMD gauge-based data for the period of 1998–2015.

	CHIRPS	MSWEP	SM2RAIN	TMPA
Correlation coefficient	0.99	0.93	0.90	0.99
RMSE (mm day^{-1})	0.40	1.17	1.64	0.43
Random error (%)	96.59	97.11	19.25	42.48
Systematic error (%)	3.41	2.89	80.75	57.52
Bias ratio	1.00	1.07	0.89	1.08
Variability ratio	1.03	1.00	0.64	1.01
KGE	0.97	0.90	0.61	0.92

covered, rainforest and high topographical areas through a static mask (Ciabatta et al., 2018). Additionally, the daily global coverage is hampered by limited temporal sampling due to the use of active and passive microwave satellite sensors (Dorigo et al., 2017). The gauge-based data set shows all-India mean precipitation as 3.01 mm day^{-1}, whereas CHIRPS, MSWEP and TMPA overestimates and SM2RAIN-CCI underestimates all-India mean precipitation values with respect to IMD gauge-based data.

Fig. 3 presents the bias in four multi-satellite precipitation products over the country as compared to gauge-based observations for the study period. Larger biases in these four multi-satellite precipitation products are evident over the northeast India due to varied orography and complex precipitation processes. The sign of bias shows an interesting feature along the west coast. A considerable underestimation of precipitation along the windward side of the Western Ghats (e.g., close to the west coast) and overestimation along the leeward side is common to these multi-satellite products. All these four multi-satellite products underestimate precipitation over the northern India (e.g., Jammu & Kashmir state). The gauge-based precipitation data set has also larger uncertainty over the northern India and northeast India due to low density of gauges over these regions (Prakash et al., 2015b).

In order to assess the variability of monthly precipitation across India among these multi-satellite products, the spatial distributions of CV are illustrated in Fig. 4. The northwest India shows larger variability in monthly precipitation, which is well-depicted by CHIRPS, MSWEP, and TMPA estimates. However, SM2RAIN-CCI is not able to represent the precipitation variability adequately across the country. One of the reasons behind this discrepancy is that SM2RAIN algorithm is unable to estimate extreme precipitation in case of soil moisture saturation (Brocca et al., 2014). Although there are some differences in magnitudes of CV among IMD, CHIRPS, MSWEP, and TMPA products, they appear to be comparable qualitatively. This analysis confirms that CHIRPS and MSWEP products could be used for the study of long-term precipitation variability with higher confidence.

The spatial distributions of correlation coefficient and RMSE obtained after the quantitative comparison of four multi-satellite precipitation products against gauge-based data set for the 18-year period are shown in Fig. 5. CHIRPS and TMPA show the largest correlation and smallest RMSE across the country except over the northern India. Similar statistical performance of CHIRPS and TMPA might be due to fact that CHIRPS product is calibrated with TMPA-3B42 estimates (Funk et al., 2015). SM2RAIN-CCI also shows reasonably high correlation and low RMSE as compared to gauge-based precipitation estimates. MSWEP shows higher correlation over the high mean precipitation regions and lower correlation over the low mean precipitation areas. In general, MSWEP and SM2RAIN-CCI exhibit rather larger RMSE than CHIRPS and TMPA products.

Moreover, the spatial distributions of error components viz., systematic and random errors in four multi-satellite precipitation products across India are presented in Fig. 6. The knowledge of these error components is very important for implementing any statistical

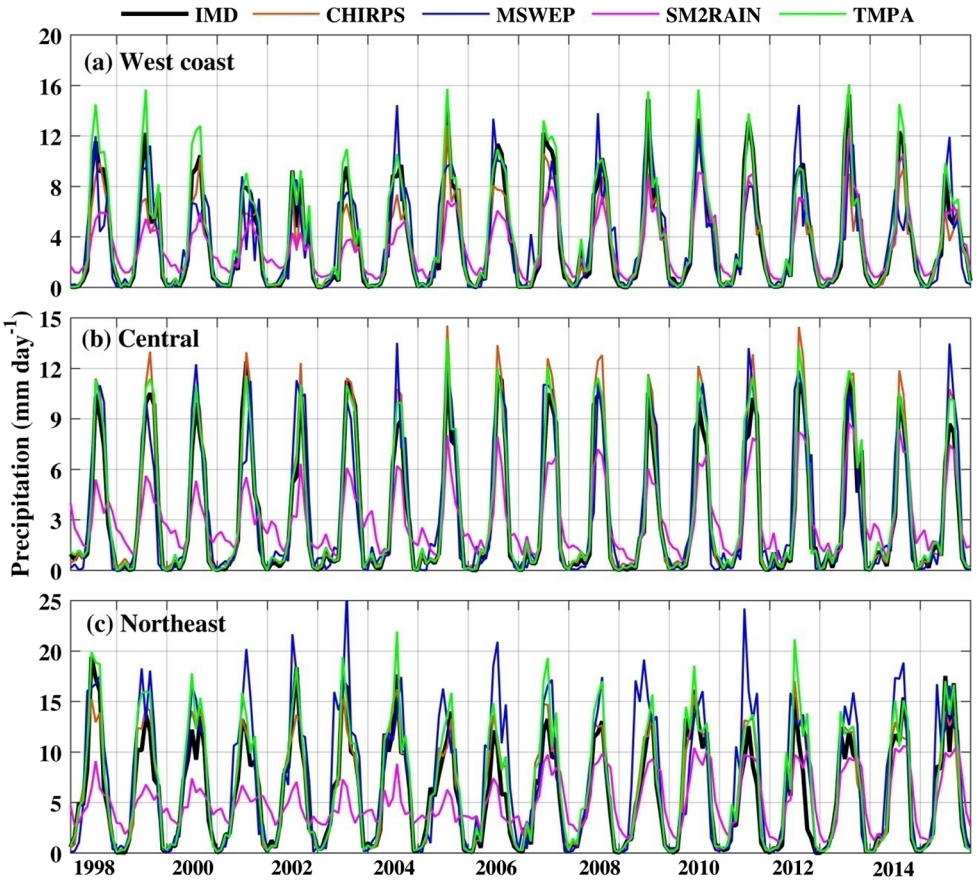

Fig. 10. Time-series of monthly domain-mean precipitation derived from the IMD, CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA products over (a) west coast, (b) central, and (c) northeast India for the period of 1998–2015.

Table 2
Error characteristics of monthly domain-mean precipitation estimates derived from CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA as compared to IMD gauge-based data over west coast, central India, and northeast India for the period of 1998–2015.

	West coast				Central India				Northeast India			
	CHIRPS	MSWEP	SM2RAIN	TMPA	CHIRPS	MSWEP	SM2RAIN	TMPA	CHIRPS	MSWEP	SM2RAIN	TMPA
Correlation coefficient	0.96	0.83	0.90	0.99	0.99	0.90	0.90	0.99	0.95	0.85	0.73	0.97
RMSE (mm day^{-1})	1.42	2.25	2.16	0.89	0.84	1.84	2.15	0.55	1.61	3.87	3.77	1.93
Random error (%)	38.20	86.11	21.37	57.89	53.08	97.40	17.35	59.72	94.19	81.53	22.41	59.09
Systematic error (%)	61.80	13.89	78.63	42.11	46.92	2.60	82.65	40.28	5.81	18.47	77.59	40.91
Bias ratio	0.87	0.99	0.87	1.13	1.11	1.07	0.94	1.09	1.06	1.28	0.88	1.18
Variability ratio	0.90	0.95	0.68	0.98	1.01	0.99	0.58	0.98	0.96	0.99	0.57	0.99
KGE	0.83	0.83	0.64	0.87	0.88	0.87	0.56	0.91	0.91	0.68	0.49	0.82

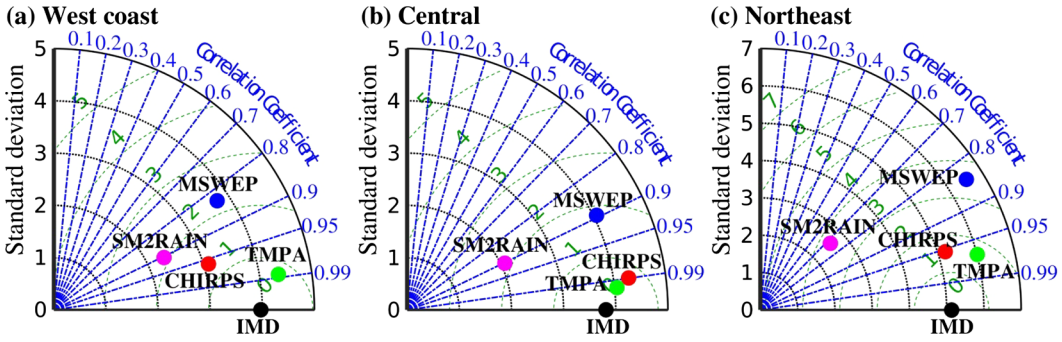

Fig. 11. Taylor diagrams comparing monthly domain-mean precipitation from CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA products with respect to IMD gauge-based data for the period of 1998–2015.

adjustments to these precipitation products before their integration in a specific application (AghaKouchak et al., 2012). Larger contributions of random error components as compared to systematic error components over the country are evident in CHIRPS, MSWEP, and TMPA products. However, SM2RAIN-CCI shows larger contribution of systematic error components than random error components. In general, CHIRPS and TMPA products are similar in terms of error characteristics and better than MSWEP product. This analysis also reveals that SM2RAIN-CCI product needs a suitable bias adjustment before integrating it in any application. Among these four multi-satellite precipitation products, SM2RAIN-CCI is the only product that does not implement any gauge-based bias correction. CHIRPS, MSWEP, and TMPA have rather smaller systematic errors due to gauge-based bias correction.

Fig. 7 presents the spatial distributions of variability ratio and KGE score in multi-satellite precipitation products as compared to gauge-based observations. CHIRPS, MSWEP, and TMPA are able to adequately capture the precipitation variability across the country except over the northern India. However, SM2RAIN-CCI largely underestimates the precipitation variability. The KGE score suggests that CHIRPS is the best performer and comparable with TMPA product. The smaller KGE score over the northern India in all precipitation products might be due to uncertainty in gauge-based estimates associated with sparse gauge density. This analysis suggests that CHIRPS product could be utilized for long-term precipitation analysis over India with higher confidence.

Fig. 8 shows the comparison of empirical CDFs among gauge-based and four multi-satellite monthly precipitation products across the country and three selected sub-regions viz., west coast, central, and northeast India for the period of 1998–2015. This analysis would show the capabilities of each satellite-based product in the estimation of different precipitation ranges as compared to ground-based observations. CHIRPS, MSWEP, and TMPA show overall good agreement with gauge-based estimates across the scale at all-India and over the central India. However, they noticeably underestimate moderate precipitation over the northeast India. SM2RAIN-CCI notably underestimates precipitation extremes and overestimates moderate precipitation. This analysis again confirms that SM2RAIN-CCI needs further improvements to make it comparable to other multi-satellite precipitation products.

Additionally, the four multi-satellite precipitation products were compared against gauge-based observations at domain-mean scale for the 18-year period. Fig. 9 shows the time-series of monthly domain-mean precipitation averaged over the entire country for the study period. The corresponding Taylor diagram is also shown to assess the error metrics of each satellite-based precipitation product. Higher all-India mean precipitation during the summer associated with the southwest monsoon is well-captured by each product. However, SM2RAIN-CCI considerably underestimates the summer precipitation and overestimates precipitation for other seasons. Table 1 presents the different error characteristics of multi-satellite precipitation as compared to gauge-based data at all-India scale. The error metrics and Taylor diagram clearly show that CHIRPS and TMPA are the best multi-satellite precipitation products followed by MSWEP, whereas SM2RAIN-CCI largely underestimates the precipitation variability and essentially needs a suitable bias adjustment.

The time-series of monthly domain-mean precipitation averaged over the west coast, central, and northeast India for the study period is presented in Fig. 10. SM2RAIN-CCI largely underestimates the summer precipitation over the central and northeast India, whereas MSWEP notably overestimates the summer precipitation over the northeast India. Table 2 presents the different error characteristics of multi-satellite precipitation as compared to gauge-based data for three sub-regions of the country. These error metrics and corresponding Taylor diagrams (e.g., Fig. 11) show TMPA and CHIRPS are comparable to gauge-based precipitation estimates over the three sub-regions. SM2RAIN-CCI underestimates precipitation variability consistently over the three sub-regions. However, MSWEP considerably overestimates precipitation over the northeast India.

4. Conclusion

In this study, performance of latest versions of four multi-satellite precipitation products – CHIRPS version 2.0, MSWEP version 2.1, SM2RAIN-CCI, TMPA version 7 were extensively assessed across India

using gauge-based observations. The assessment was done at all-India and sub-regional scales for the period of 1998–2015 at monthly scale. Results indicated that CHIRPS and TMPA were better comparable to gauge-based precipitation estimates than MSWEP estimates at all-India and sub-regional scales, which was evident from higher correlation and KGE score, and lower bias and RMSE with respect to gauge-based precipitation data. These multi-satellite precipitation products were able to capture the precipitation gradients along the west coast of India. However, SM2RAIN-CCI largely underestimated precipitation variability across the country as compared to gauge-based observations. This surface soil moisture derived precipitation product notably underestimated the summer monsoon precipitation and overestimated precipitation for other seasons. Furthermore, the systematic error component in SM2RAIN-CCI dominated than the random error component, which suggested the need of a suitable bias correction to this precipitation product before integrating it in any application. The overall results indicated better performance of CHIRPS data set for long-term precipitation analysis. However, there is a need to comprehensively evaluate these precipitation products along with GPM-based IMERG data set at daily time scale for hydrometeorological applications. Furthermore, multi-satellite precipitation products used to be reprocessed with some improvements eventually and updated version gets released, which essentially needs to be comprehensively evaluated before integrating them to any specific application.

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